ENV 790.30 - Time Series Analysis for Energy Data | Spring 2022

Assignment 3 - Due date 02/08/22

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Directions

You should open the .rmd file corresponding to this assignment on RStudio. The file is available on our class repository on Github.

Once you have the project open the first thing you will do is change "Student Name" on line 3 with your name. Then you will start working through the assignment by **creating code and output** that answer each question. Be sure to use this assignment document. Your report should contain the answer to each question and any plots/tables you obtained (when applicable).

Please keep this R code chunk options for the report. It is easier for us to grade when we can see code and output together. And the tidy.opts will make sure that line breaks on your code chunks are automatically added for better visualization.

When you have completed the assignment, **Knit** the text and code into a single PDF file. Rename the pdf file such that it includes your first and last name (e.g., "LuanaLima_TSA_A03_Sp22.Rmd"). Submit this pdf using Sakai.

Questions

Consider the same data you used for A2 from the spreadsheet "Table_10.1_Renewable_Energy_Production_and_Consumption_by_Source.xlsx". The data comes from the US Energy Information and Administration and corresponds to the January 2022 **Monthly** Energy Review. Once again you will work only with the following columns: Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption. Create a data frame structure with these three time series only.

R packages needed for this assignment:"forecast","tseries", and "Kendall". Install these packages, if you haven't done yet. Do not forget to load them before running your script, since they are NOT default packages.

Set Up

```
#Importing data set
energy_data <- read.xlsx(file="../Data/Table_10.1_Renewable_Energy_Production
_and_Consumption_by_Source.xlsx",header=FALSE, startRow=13, sheetIndex=1)
#extracting column names from row 11
read_col_names <- read.xlsx(file="../Data/Table_10.1_Renewable_Energy_Product
ion_and_Consumption_by_Source.xlsx",header=FALSE,startRow=11,endRow=11,sheetI
```

```
ndex=1)
colnames(energy_data) <- read_col_names
head(energy_data)
```

```
##        Month Wood Energy Production Biofuels Production
## 1 1973-01-01                129.630       Not Available
## 2 1973-02-01                117.194       Not Available
## 3 1973-03-01                129.763       Not Available
## 4 1973-04-01                125.462       Not Available
## 5 1973-05-01                129.624       Not Available
## 6 1973-06-01                125.435       Not Available
##   Total Biomass Energy Production Total Renewable Energy Production
## 1                         129.787                           403.981
## 2                         117.338                           360.900
## 3                         129.938                           400.161
## 4                         125.636                           380.470
## 5                         129.834                           392.141
## 6                         125.611                           377.232
##   Hydroelectric Power Consumption Geothermal Energy Consumption
## 1                         272.703                         1.491
## 2                         242.199                         1.363
## 3                         268.810                         1.412
## 4                         253.185                         1.649
## 5                         260.770                         1.537
## 6                         249.859                         1.763
##   Solar Energy Consumption Wind Energy Consumption Wood Energy Consumption
## 1            Not Available           Not Available                 129.630
## 2            Not Available           Not Available                 117.194
## 3            Not Available           Not Available                 129.763
## 4            Not Available           Not Available                 125.462
## 5            Not Available           Not Available                 129.624
## 6            Not Available           Not Available                 125.435
##   Waste Energy Consumption Biofuels Consumption
## 1                    0.157        Not Available
## 2                    0.144        Not Available
## 3                    0.176        Not Available
## 4                    0.174        Not Available
## 5                    0.210        Not Available
## 6                    0.176        Not Available
##   Total Biomass Energy Consumption Total Renewable Energy Consumption
## 1                          129.787                            403.981
## 2                          117.338                            360.900
## 3                          129.938                            400.161
## 4                          125.636                            380.470
## 5                          129.834                            392.141
## 6                          125.611                            377.232
```

```
#creating df structure for columns of interest
df <- energy_data[,c('Month','Total Biomass Energy Production', 'Total Renewa
```

```
ble Energy Production','Hydroelectric Power Consumption')]
head(df)
```

```
##        Month Total Biomass Energy Production Total Renewable Energy Produc
tion
## 1 1973-01-01                         129.787                           403
.981
## 2 1973-02-01                         117.338                           360
.900
## 3 1973-03-01                         129.938                           400
.161
## 4 1973-04-01                         125.636                           380
.470
## 5 1973-05-01                         129.834                           392
.141
## 6 1973-06-01                         125.611                           377
.232
##   Hydroelectric Power Consumption
## 1                         272.703
## 2                         242.199
## 3                         268.810
## 4                         253.185
## 5                         260.770
## 6                         249.859
```

```
#transforming data into time series
ts_energy_data <- ts(data=df[,2:4], start=c(1973,1),frequency=12)
head(ts_energy_data)
```

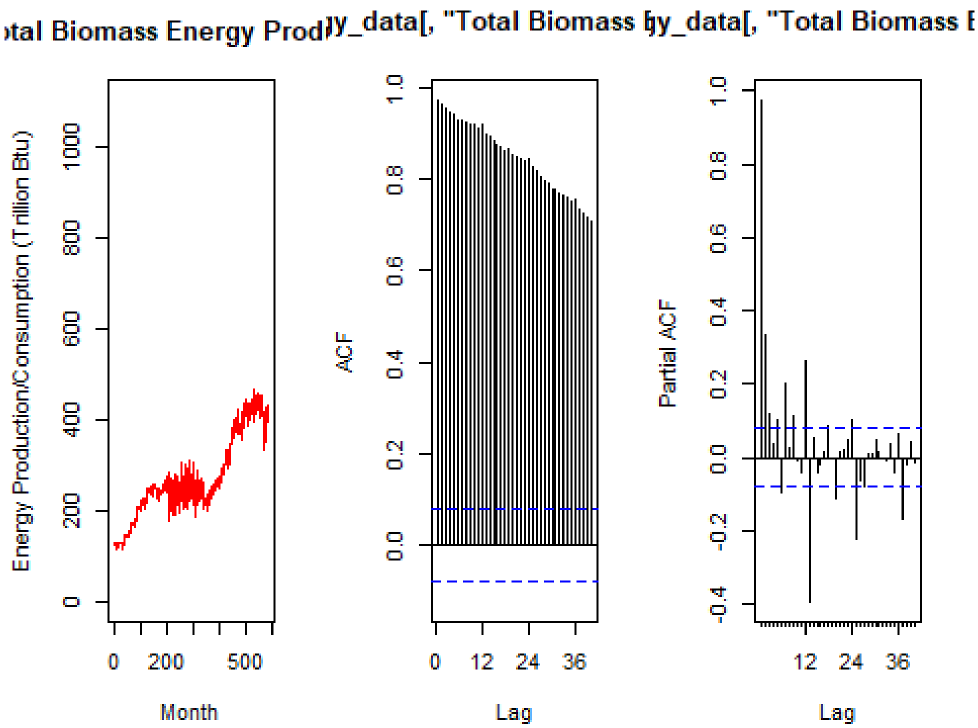
```
##          Total Biomass Energy Production Total Renewable Energy Production
## Jan 1973                         129.787                           403.981
## Feb 1973                         117.338                           360.900
## Mar 1973                         129.938                           400.161
## Apr 1973                         125.636                           380.470
## May 1973                         129.834                           392.141
## Jun 1973                         125.611                           377.232
##          Hydroelectric Power Consumption
## Jan 1973                         272.703
## Feb 1973                         242.199
## Mar 1973                         268.810
## Apr 1973                         253.185
## May 1973                         260.770
## Jun 1973                         249.859
```

Trend Component

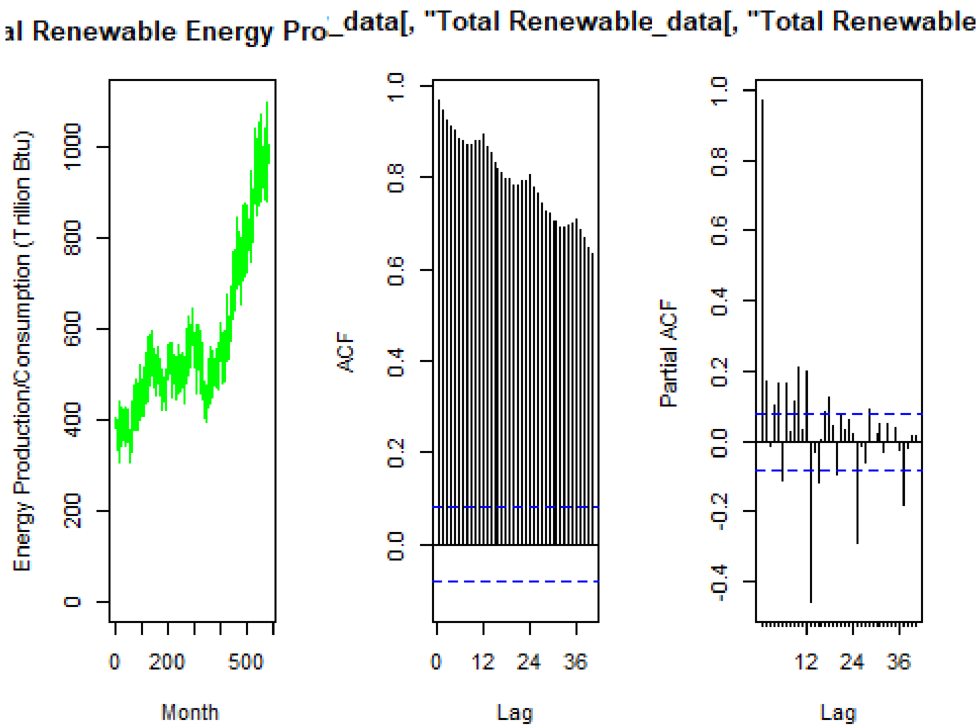
Q1

Create a plot window that has one row and three columns. And then for each object on your data frame, fill the plot window with time series plot, ACF and PACF. You may use the some code from A2, but I want all three plots on the same window this time. (Hint: use par() function)

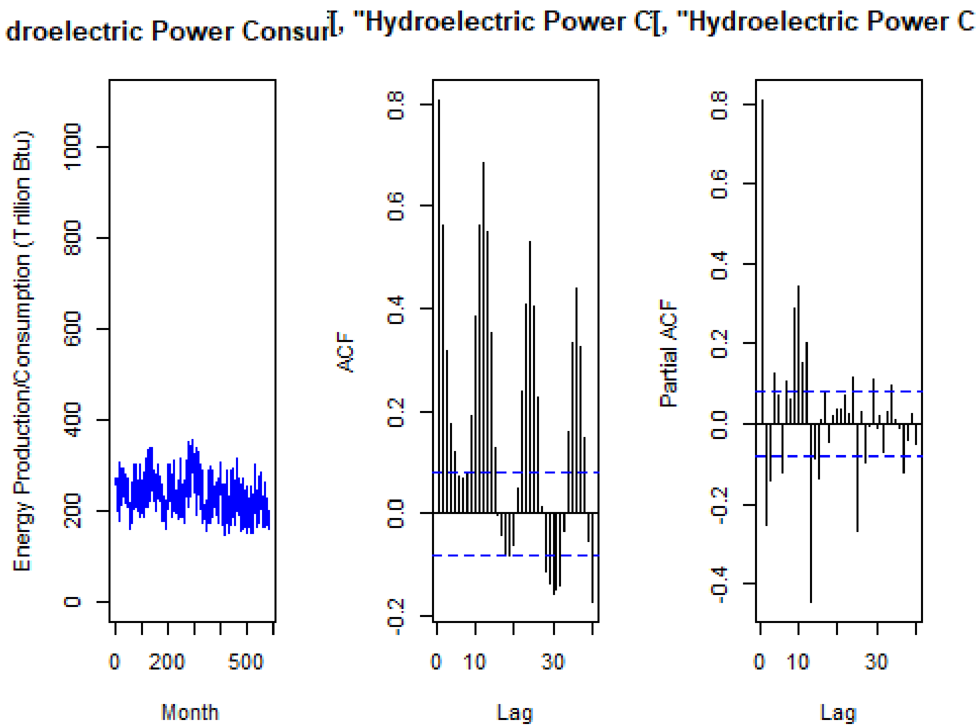
```
#time series, ACF, and PACF

par(mfrow=c(1,3))
plot(df[,"Total Biomass Energy Production"],type="l",col="red",ylab="Energy P
roduction/Consumption (Trillion Btu)", xlab="Month", ylim=c(0,1100))
title(main="Total Biomass Energy Production")
Acf(ts_energy_data[,"Total Biomass Energy Production"],lag.max=40, type="corr
elation", plot=TRUE)
Pacf(ts_energy_data[,"Total Biomass Energy Production"],lag.max=40, plot=TRUE
)
```




```
par(mfrow=c(1,3))
plot(df[,"Total Renewable Energy Production"],type="l",col="green",ylab="Ener
gy Production/Consumption (Trillion Btu)", xlab="Month", ylim=c(0,1100))
title(main="Total Renewable Energy Production")
Acf(ts_energy_data[,"Total Renewable Energy Production"],lag.max=40, type="co
rrelation", plot=TRUE)
Pacf(ts_energy_data[,"Total Renewable Energy Production"],lag.max=40, plot=TR
UE)
```




```
par(mfrow=c(1,3))  #place three plots in the same window.
plot(df[,"Hydroelectric Power Consumption"],type="l",col="blue",ylab="Energy
Production/Consumption (Trillion Btu)", xlab="Month", ylim=c(0,1100))
title(main="Hydroelectric Power Consumption")
Acf(df[,"Hydroelectric Power Consumption"],lag.max=40, type="correlation", pl
ot=TRUE)
Pacf(df[,"Hydroelectric Power Consumption"],lag.max=40, plot=TRUE)
```



Q2

From the plot in Q1, do the series Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption appear to have a trend? If yes, what kind of trend?

Total Biomass Energy Production has an increasing trend. Total Renewable Energy Production also has an increasing trend. Hydroelectric Power Consumption's data appears to have a slight decreasing trend and a much more obvious seasonality.

Q3

Use the *lm()* function to fit a linear trend to the three time series. Ask R to print the summary of the regression. Interpret the regression output, i.e., slope and intercept. Save the regression coefficients for further analysis.

```
#Create vector t
nobs=nrow(df)
t <- c(1:nobs)

#Fit a linear trend to TS of Total Biomass
linear_trend_model_bio=lm(df[,2]~t)
summary(linear_trend_model_bio)

##
## Call:
## lm(formula = df[, 2] ~ t)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -101.892  -24.306    4.932   33.103   82.292
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.348e+02  3.282e+00   41.07   <2e-16 ***
## t           4.744e-01  9.705e-03   48.88   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.64 on 583 degrees of freedom
## Multiple R-squared:  0.8039, Adjusted R-squared:  0.8035
## F-statistic:  2389 on 1 and 583 DF,  p-value: < 2.2e-16

beta0b=as.numeric(linear_trend_model_bio$coefficients[1])  #first coefficient
is the intercept term or beta0
beta1b=as.numeric(linear_trend_model_bio$coefficients[2])  #second coefficien
t is the slope or beta1
```

The slope of Total Biomass Energy Production has a slightly positive slope indicating a correlation between time and Biomass Energy Production e.g. a slightly increasing trend. The intercept is a large positive number indicating that at the beginning of the time series (e.g. in 1973), 134.80 trillion Btus of Biomass Energy was being produced.

```
#Fit a linear trend to TS of Total Renewable Energy Production
linear_trend_model_renew=lm(df[,3]~t)
summary(linear_trend_model_renew)

##
## Call:
## lm(formula = df[, 3] ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -230.488  -57.869    5.595   62.090  261.349
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 323.18243    8.02555   40.27   <2e-16 ***
## t             0.88051    0.02373   37.10   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 96.93 on 583 degrees of freedom
## Multiple R-squared:  0.7025, Adjusted R-squared:  0.702
## F-statistic:  1377 on 1 and 583 DF,  p-value: < 2.2e-16

beta0r=as.numeric(linear_trend_model_renew$coefficients[1])  #first coefficie
nt is the intercept term or beta0
```

```
beta1r=as.numeric(linear_trend_model_renew$coefficients[2])  #second coeffici
ent is the slope or beta1
```

The slope of Total Renewable Energy Production has a slightly positive slope indicating a correlation between time and Renewable Energy Production, e.g. the data has a slightly increasing trend. The intercept is a large positive number indicating that at the beginning of the time series (e.g. in 1973), 323.18 trillion Btus of Renewable Energy was being produced.

```
#Fit a linear trend to TS of Hydroelectric Power Consumption
linear_trend_model_hydro=lm(df[,4]~t)
summary(linear_trend_model_hydro)

## 
## Call:
## lm(formula = df[, 4] ~ t)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -94.892 -31.300  -2.414  27.876 121.263 
## 
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 259.18303    3.47464  74.593  < 2e-16 ***
## t            -0.07924    0.01027  -7.712 5.36e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 41.97 on 583 degrees of freedom
## Multiple R-squared:  0.09258,    Adjusted R-squared:  0.09103 
## F-statistic: 59.48 on 1 and 583 DF,  p-value: 5.364e-14

beta0h=as.numeric(linear_trend_model_hydro$coefficients[1])  #first coefficie
nt is the intercept term or beta0
beta1h=as.numeric(linear_trend_model_hydro$coefficients[2])  #second coeffici
ent is the slope or beta1
```

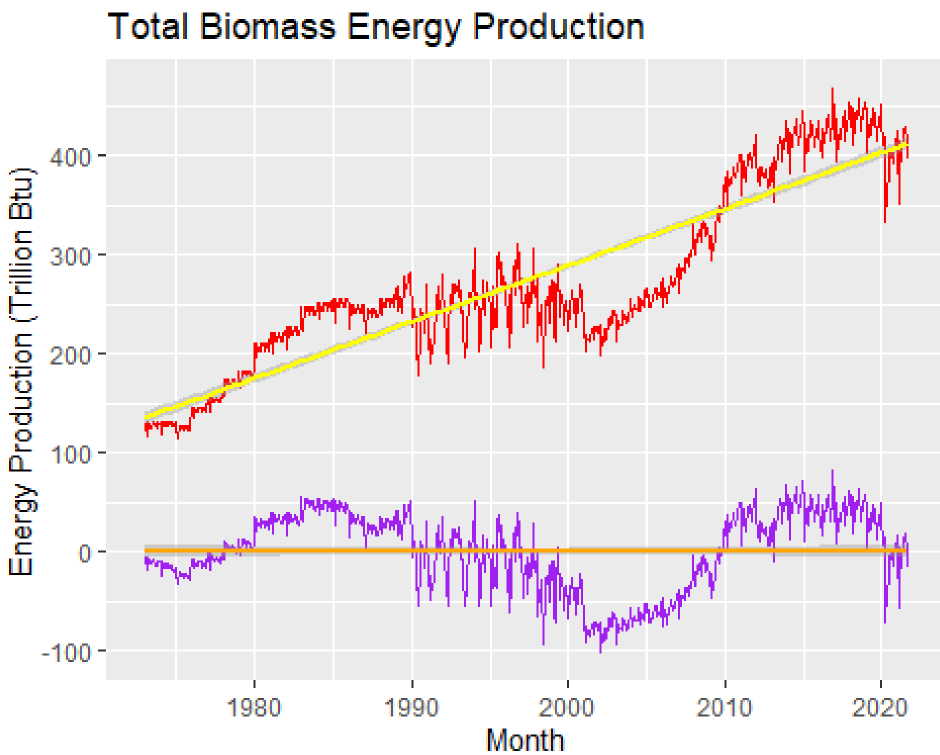
The slope of Hydroelectric Power Consumption has a slightly negative slope indicating that the data has a slightly decreasing trend. The intercept is a large positive number indicating that at the beginning of the time series (e.g. in 1973), 259.18 trillion Btus of Hydroelectric power was being consumed.

Q4

Use the regression coefficients from Q3 to detrend the series. Plot the detrended series and compare with the plots from Q1. What happened? Did anything change?

```
#remove the trend from TS of Total Biomass Energy Production
detrend_bio_data <- df[,2]-(beta0b+beta1b*t)

#plotting detrended series
```

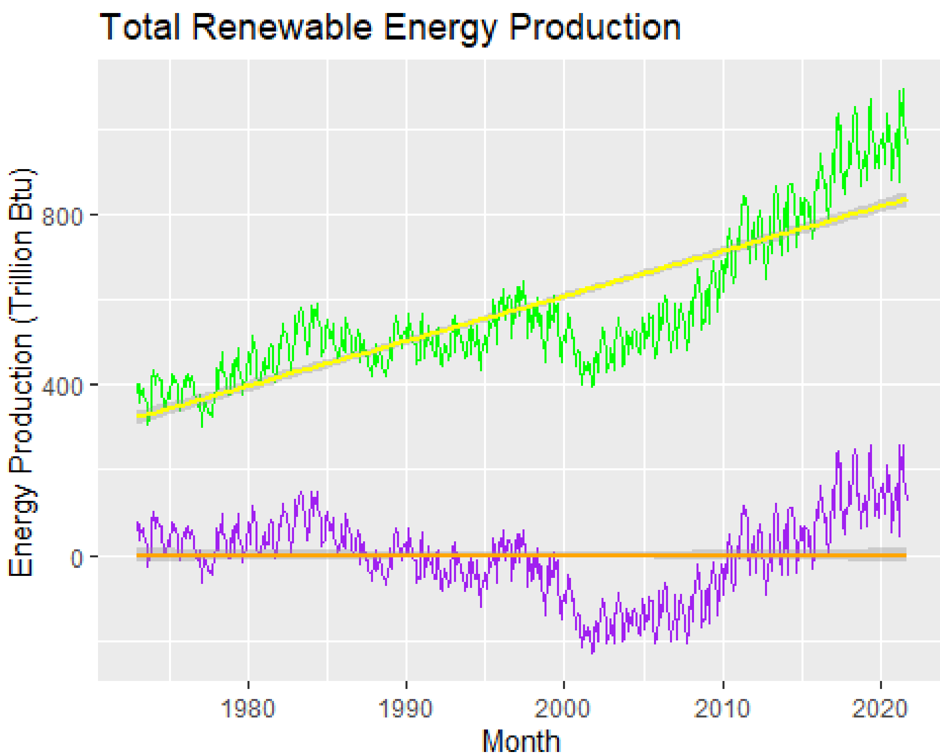
```
ggplot(df, aes(x=df[,1], y=df[,"Total Biomass Energy Production"])) +
            geom_line(color="red") +
            ggtitle("Total Biomass Energy Production")+
            ylab(paste0("Energy Production (Trillion Btu)")) +
            xlab(paste0("Month"))+
            geom_smooth(color="yellow",method="lm") +
            geom_line(aes(y=detrend_bio_data), col="purple")+
            geom_smooth(aes(y=detrend_bio_data),color="orange",method="lm")

## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



The increasing trend was removed from the Total Biomass Energy Production series.

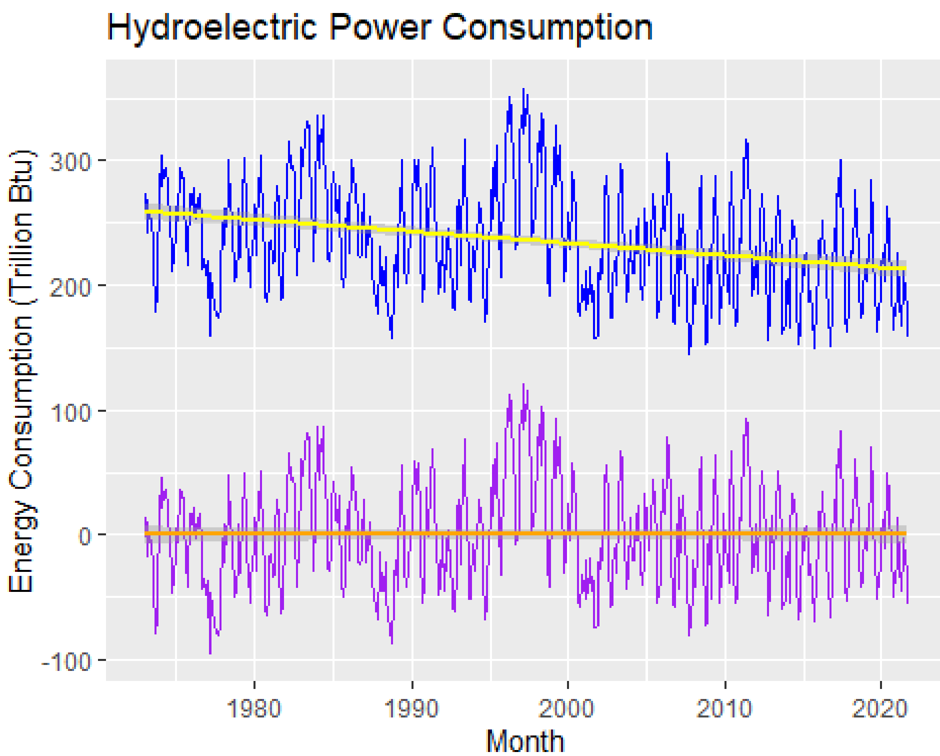
```
#remove the trend from TS of Total Renewable Energy Production
detrend_renew_data <- df[,3]-(beta0r+beta1r*t)

#plotting detrended series
ggplot(df, aes(x=df[,1], y=df[,"Total Renewable Energy Production"])) +
            geom_line(color="green") +
            ggtitle("Total Renewable Energy Production")+
            ylab(paste0("Energy Production (Trillion Btu)")) +
            xlab(paste0("Month"))+
            geom_smooth(color="yellow",method="lm") +
            geom_line(aes(y=detrend_renew_data), col="purple")+
            geom_smooth(aes(y=detrend_renew_data),color="orange",method="lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



The increasing trend was removed from the Total Renewable Energy Production series.

```
#remove the trend from TS of Hydroelectric Power Consumption
detrend_hydro_data <- df[,4]-(beta0h+beta1h*t)

#plotting detrended series
ggplot(df, aes(x=df[,1], y=df[,"Hydroelectric Power Consumption"])) +
            geom_line(color="blue") +
            ggtitle("Hydroelectric Power Consumption")+
            ylab(paste0("Energy Consumption (Trillion Btu)")) +
            xlab(paste0("Month"))+
            geom_smooth(color="yellow",method="lm") +
            geom_line(aes(y=detrend_hydro_data), col="purple")+
            geom_smooth(aes(y=detrend_hydro_data),color="orange",method="lm")

## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```

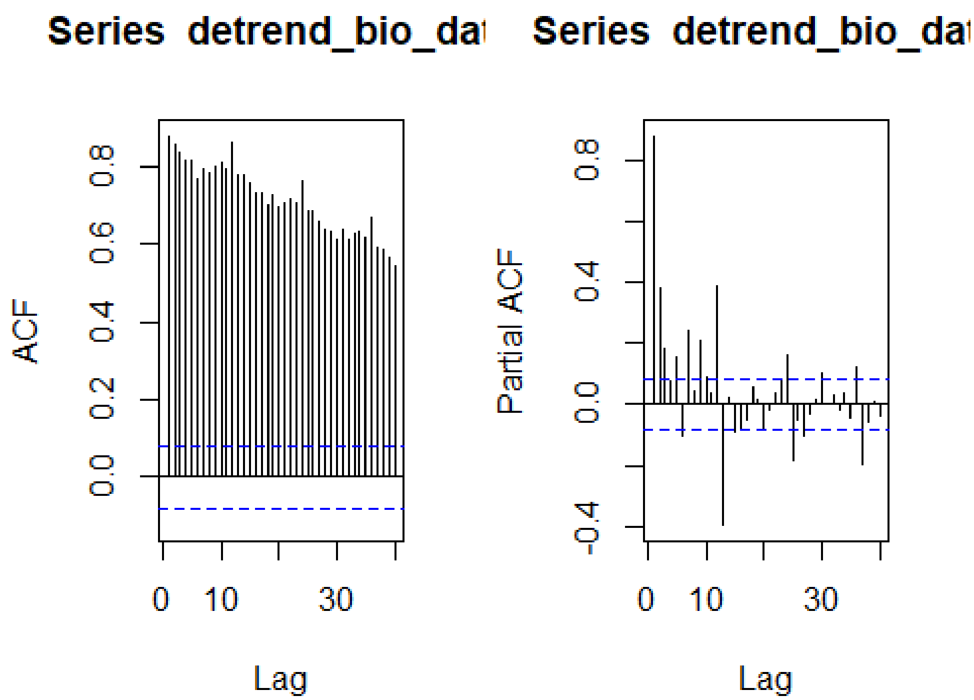


The very slight decreasing trend was removed from the Hydroelectric Power Consumption series.

Q5

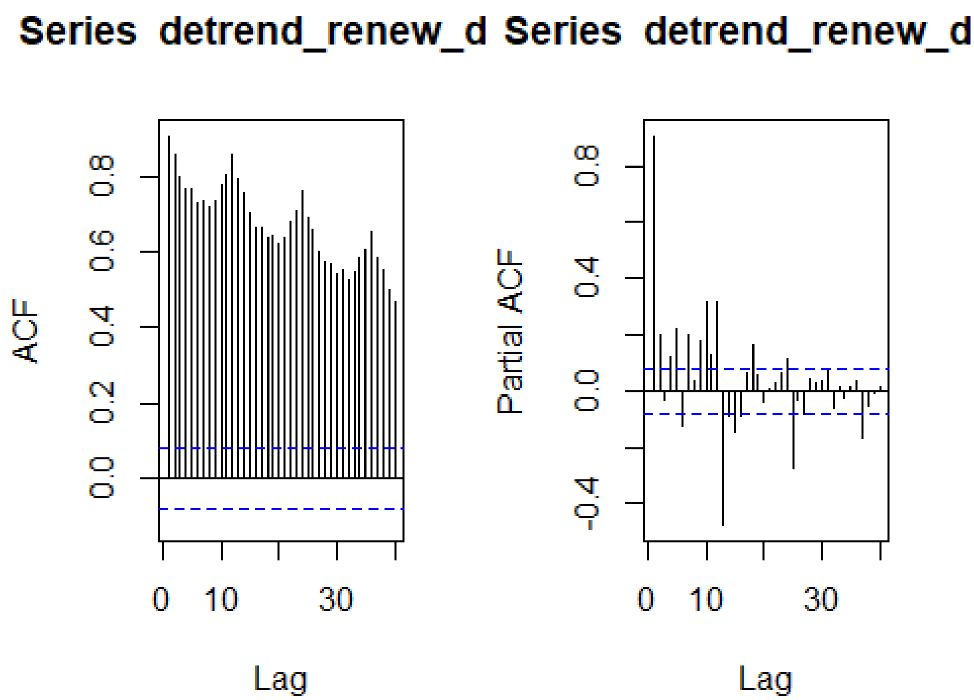
Plot ACF and PACF for the detrended series and compare with the plots from Q1. Did the plots change? How?

```r
#new ACF and PACF of Total Biomass Energy Production
par(mfrow=c(1,2))
Acf(detrend_bio_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(detrend_bio_data,lag.max=40, plot=TRUE)
```



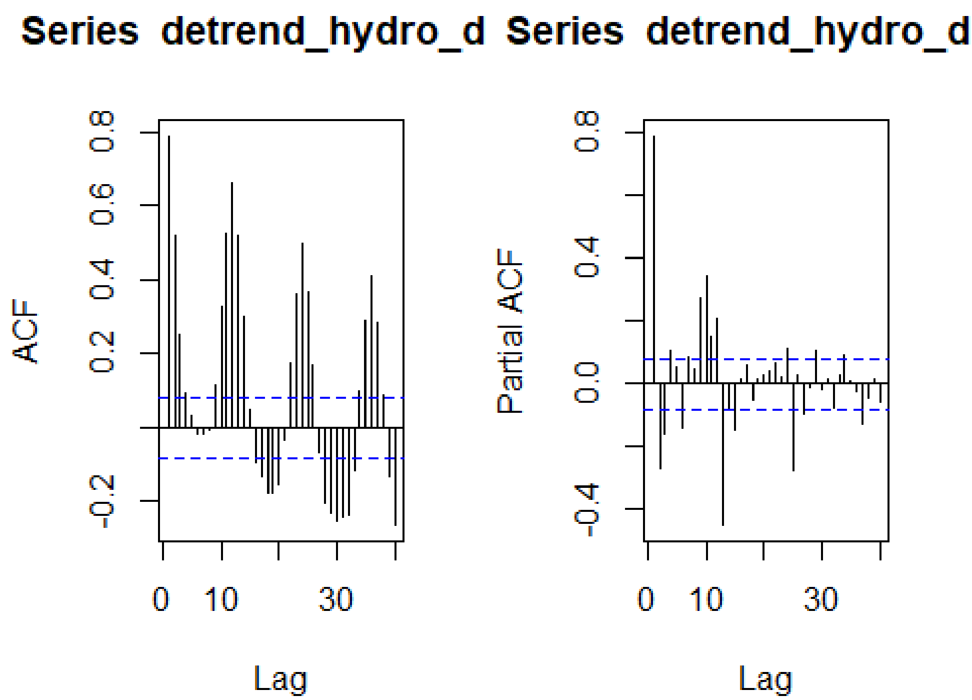
The ACF shows that the values of the detrended series are less related with its past values than that of the orignal series. The PACF shows that there is a greater correlation between the lags of the series when it is detrended than that of the original series.

```
#new ACF and PACF of Total Renewable Energy Production
par(mfrow=c(1,2))
Acf(detrend_renew_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(detrend_renew_data,lag.max=40, plot=TRUE)
```



The ACF shows that the values of the detrended series are less related with its past values than that of the orignal series and that there might be greater seasonality. The PACF looks pretty similar to that of the original series possibly indicating that the lags in the detrended series have a similar correlation to that of the original series.

```
#new ACF and PACF of Hydroelectric Power Consumption
par(mfrow=c(1,2))
Acf(detrend_hydro_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(detrend_hydro_data,lag.max=40, plot=TRUE)
```



The ACF and PACF of the detrended series look similar to that of the original series. The ACF of the detrended series looks like it has slightly greater correlation than that of the PACF but I am not sure it is significant. Overall, we can deduce that the minor decreasing trend in this series has minimal impact upon the correlation of the series.

Seasonal Component

Set aside the detrended series and consider the original series again from Q1 to answer Q6 to Q8.

Q6

Do the series seem to have a seasonal trend? Which serie/series? Use function *lm()* to fit a seasonal means model (i.e. using the seasonal dummies) to this/these time series. Ask R to print the summary of the regression. Interpret the regression output. Save the regression coefficients for further analysis.

The Hydroelectric Power Consumption series appears to have the most obvious seasonal trend.

```
#Using seasonal means model
#Creating the seasonal dummies
dummies <- seasonaldummy(ts_energy_data[,3])  #bc this function only accepts
ts object

#Fitting a linear model to the seasonal dummies
```

```
seas_means_model=lm(df[,4]~dummies)
summary(seas_means_model)
```

```
##
## Call:
## lm(formula = df[, 4] ~ dummies)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -90.253 -23.017  -3.042  21.487  99.478
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  237.841      4.892  48.616  < 2e-16 ***
## dummiesJan    13.558      6.883   1.970  0.04936 *
## dummiesFeb    -8.090      6.883  -1.175  0.24037
## dummiesMar    20.067      6.883   2.915  0.00369 **
## dummiesApr    16.619      6.883   2.414  0.01607 *
## dummiesMay    39.961      6.883   5.805 1.06e-08 ***
## dummiesJun    31.315      6.883   4.549 6.57e-06 ***
## dummiesJul    10.511      6.883   1.527  0.12732
## dummiesAug   -17.853      6.883  -2.594  0.00974 **
## dummiesSep   -49.852      6.883  -7.242 1.43e-12 ***
## dummiesOct   -48.086      6.919  -6.950 9.96e-12 ***
## dummiesNov   -32.187      6.919  -4.652 4.08e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.89 on 573 degrees of freedom
## Multiple R-squared:  0.4182, Adjusted R-squared:  0.4071
## F-statistic: 37.45 on 11 and 573 DF,  p-value: < 2.2e-16
```

March through July appear to be more positively correlated, possibly indicating a wet period where there is more hydroelectric power available to produce or a greater demand for hydroelectric power. Since August through November are negative, we can assume that is a either a more dry period or less demand for hydroelectric power (or both).

The Total Renewable Energy Production series appears to have a slight seasonal trend as well.

```
#Using seasonal means model
#Creating the seasonal dummies
dummiesr <- seasonaldummy(ts_energy_data[,2])  #bc this function only accepts
ts object

#Fitting a linear model to the seasonal dummies
seas_means_model_renew=lm(df[,3]~dummiesr)
summary(seas_means_model_renew)
```

```
##
## Call:
## lm(formula = df[, 3] ~ dummiesr)
##
## Residuals:
##      Min       1Q  Median      3Q     Max
## -272.95 -111.55  -59.35   65.68  480.41
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  589.971     25.464  23.169   <2e-16 ***
## dummiesrJan   11.793     35.828   0.329   0.7422
## dummiesrFeb  -40.992     35.828  -1.144   0.2530
## dummiesrMar   21.892     35.828   0.611   0.5414
## dummiesrApr    8.908     35.828   0.249   0.8037
## dummiesrMay   37.500     35.828   1.047   0.2957
## dummiesrJun   19.465     35.828   0.543   0.5871
## dummiesrJul    8.115     35.828   0.227   0.8209
## dummiesrAug  -18.359     35.828  -0.512   0.6086
## dummiesrSep  -62.115     35.828  -1.734   0.0835 .
## dummiesrOct  -51.377     36.012  -1.427   0.1542
## dummiesrNov  -41.789     36.012  -1.160   0.2464
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 176.4 on 573 degrees of freedom
## Multiple R-squared:  0.03139,    Adjusted R-squared:  0.0128
## F-statistic: 1.688 on 11 and 573 DF,  p-value: 0.07235
```

Indeed, there appears to be a slight seasonality in Renewables production with greater correlation in the summer (March through July) and a more negative correlation in the fall/winter (August - November). I would presume this is due to solar consumption, but more inspection of the sources of data would be needed.

To be exhaustive, I looked at the seasonality of the Total Biomass Energy Production series as well.

```
#Using seasonal means model
#Creating the seasonal dummies
dummiesb <- seasonaldummy(ts_energy_data[,1])  #bc this function only accepts
ts object

#Fitting a linear model to the seasonal dummies
seas_means_model_bio=lm(df[,2]~dummiesb)
summary(seas_means_model_bio)
```

```
##
## Call:
## lm(formula = df[, 2] ~ dummiesb)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -156.96  -51.40  -22.15   60.65  183.31 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  284.241     12.962  21.928   <2e-16 ***
## dummiesbJan   -1.498     18.238  -0.082   0.9346    
## dummiesbFeb  -30.582     18.238  -1.677   0.0941 .  
## dummiesbMar   -8.873     18.238  -0.486   0.6268    
## dummiesbApr  -21.009     18.238  -1.152   0.2498    
## dummiesbMay  -14.065     18.238  -0.771   0.4409    
## dummiesbJun  -19.601     18.238  -1.075   0.2829    
## dummiesbJul   -3.499     18.238  -0.192   0.8479    
## dummiesbAug   -0.252     18.238  -0.014   0.9890    
## dummiesbSep  -12.518     18.238  -0.686   0.4928    
## dummiesbOct   -3.629     18.331  -0.198   0.8432    
## dummiesbNov   -9.592     18.331  -0.523   0.6010    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 89.81 on 573 degrees of freedom
## Multiple R-squared:  0.01056,    Adjusted R-squared:  -0.008439 
## F-statistic: 0.5557 on 11 and 573 DF,  p-value: 0.8647
```

I am not seeing any seasonality trend from the regression coefficients for Biomass Energy Production.

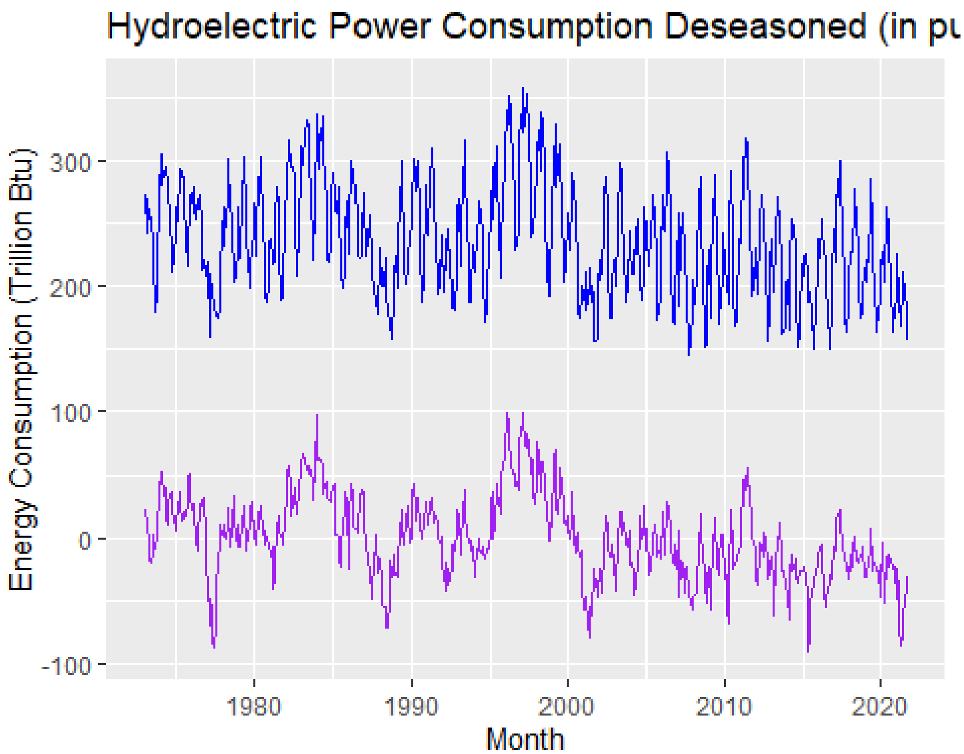
```r
#Storing regression coefficients
beta_inth=seas_means_model$coefficients[1]
beta_coeffh=seas_means_model$coefficients[2:12]

beta_intr=seas_means_model_renew$coefficients[1]
beta_coeffr=seas_means_model_renew$coefficients[2:12]

beta_intb=seas_means_model_bio$coefficients[1]
beta_coeffb=seas_means_model_bio$coefficients[2:12]
```

Q7

Use the regression coefficients from Q6 to deseason the series. Plot the deseason series and compare with the plots from part Q1. Did anything change?

```r
#Computing seasonal component for Hydro
hydro_seas_comp=array(0,nobs)
for(i in 1:nobs){
  hydro_seas_comp[i]=(beta_inth+beta_coeffh%*%dummies[i,])
}

#Removing seasonal component
```

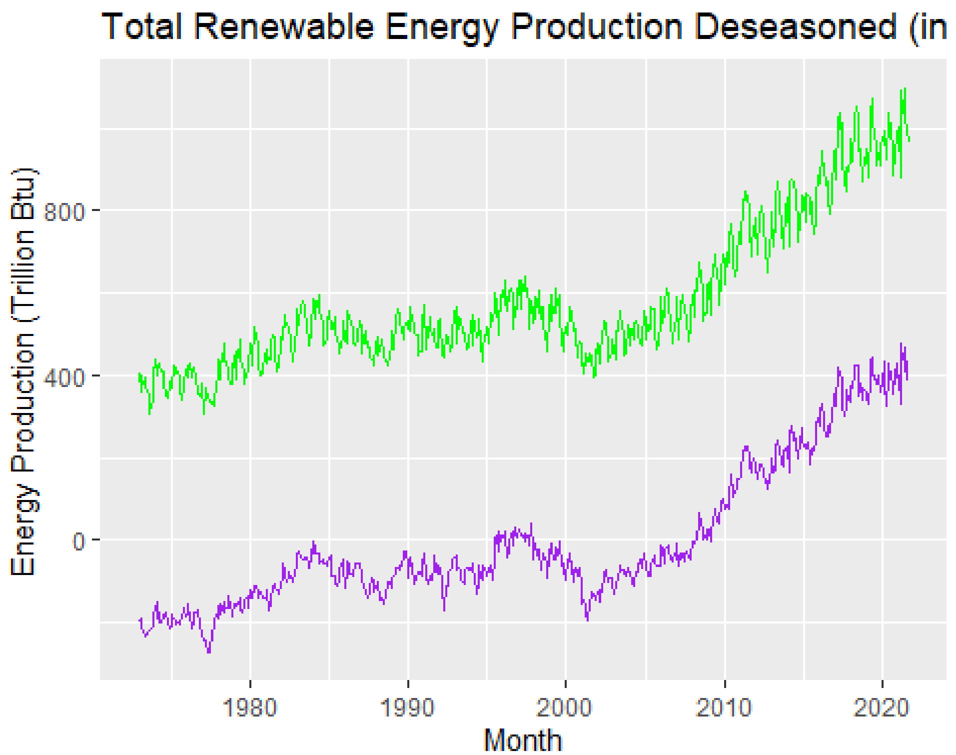
```
deseason_hydro_data <- df[,4]-hydro_seas_comp


#Graphing
ggplot(df, aes(x=df[,1], y=df[,"Hydroelectric Power Consumption"])) +
            ggtitle("Hydroelectric Power Consumption Deseasoned (in purple)")
+
            geom_line(color="blue") +
            ylab(paste0("Energy Consumption (Trillion Btu)")) +
            xlab(paste0("Month"))+
            geom_line(aes(y=deseason_hydro_data), col="purple")
```



Yes, the plot changed to where the slope of the data appears to be more closely centered around 0 than the original series.

```
#Computing seasonal component for Renewables Production
renew_seas_comp=array(0,nobs)
for(i in 1:nobs){
  renew_seas_comp[i]=(beta_intr+beta_coeffr%*%dummies[i,])
}

#Removing seasonal component
deseason_renew_data <- df[,3]-renew_seas_comp


#Graphing
```

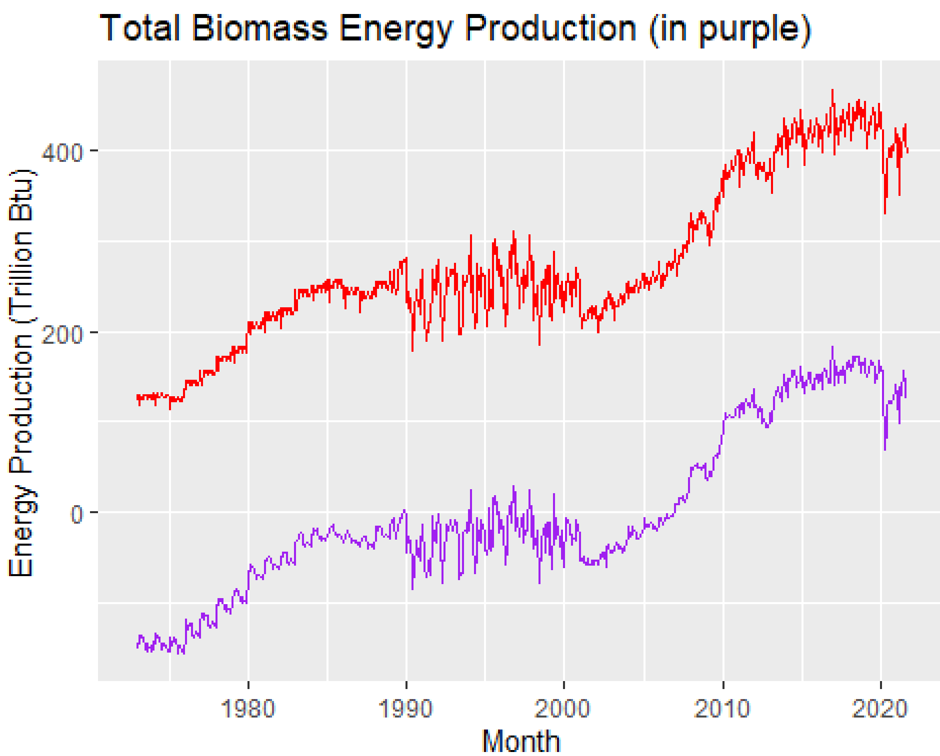
```
ggplot(df, aes(x=df[,1], y=df[,"Total Renewable Energy Production"])) +
            ggtitle("Total Renewable Energy Production Deseasoned (in purple)
")+
            geom_line(color="green") +
            ylab(paste0("Energy Production (Trillion Btu)")) +
            xlab(paste0("Month"))+
            geom_line(aes(y=deseason_renew_data), col="purple")
```



There does not appear to be much of a change between the two graphs regarding trends with various time points. Therefore, it could be concluded that deseasoning is not the best way to analyze this series.

```
#Computing seasonal component for Biomass Energy Production
bio_seas_comp=array(0,nobs)
for(i in 1:nobs){
  bio_seas_comp[i]=(beta_intb+beta_coeffb%*%dummies[i,])
}

#Removing seasonal component
deseason_bio_data <- df[,2]-bio_seas_comp


#Graphing
ggplot(df, aes(x=df[,1], y=df[,"Total Biomass Energy Production"])) +
            ggtitle("Total Biomass Energy Production (in purple)")+
            geom_line(color="red") +
```

```
        ylab(paste0("Energy Production (Trillion Btu)")) +
        xlab(paste0("Month"))+
        geom_line(aes(y=deseason_bio_data), col="purple")
```

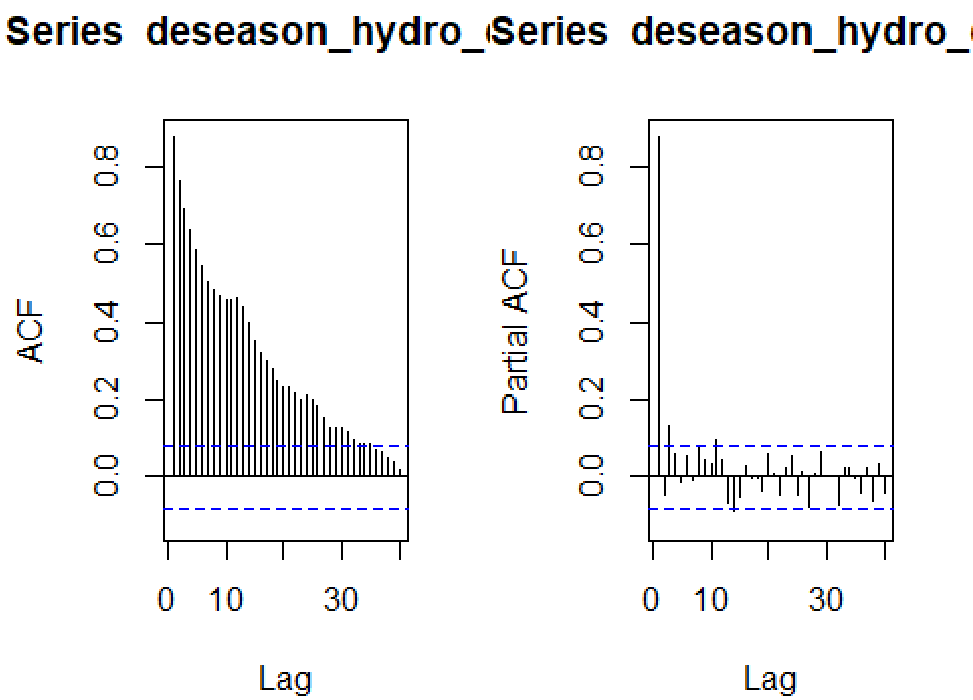


There does not appear any change between the two graphs regarding trends with various time points. Therefore, it could be concluded that deseasoning is not recommended for analyzing this series.

Q8

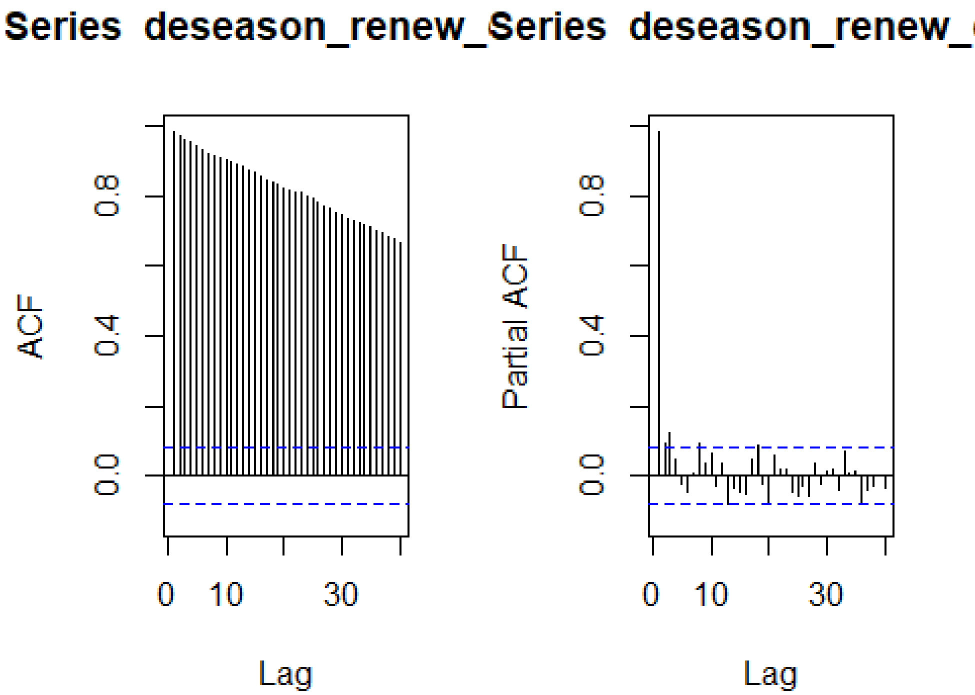
Plot ACF and PACF for the deseason series and compare with the plots from Q1. Did the plots change? How?

```
#new ACF and PACF of Hydroelectric Power Consumption
par(mfrow=c(1,2))
Acf(deseason_hydro_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(deseason_hydro_data,lag.max=40, plot=TRUE)
```



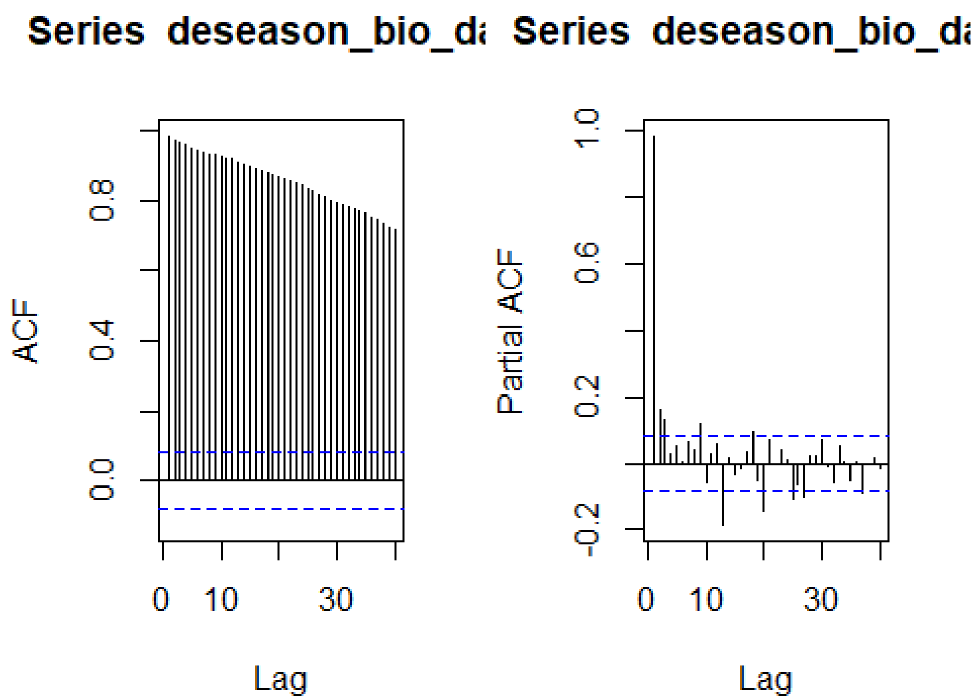
The ACF has no seasonal correlation unlike the original series. The PACF shows no significant correlation between the lags of the deseasoned data.

```
#new ACF and PACF of Total Renewable Energy Production
par(mfrow=c(1,2))
Acf(deseason_renew_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(deseason_renew_data,lag.max=40, plot=TRUE)
```



The ACF has less of a seasonal correlation unlike the original series, but still has a few spikes that could indicate a different trend. The PACF looks very similar to the plot from Q1 perhaps indicating that the lags are still correlated to one another in what appears to be a seasonal manner (once a year).

```
#new ACF and PACF of Biomass Energy Production
par(mfrow=c(1,2))
Acf(deseason_bio_data,lag.max=40, type="correlation", plot=TRUE)
Pacf(deseason_bio_data,lag.max=40, plot=TRUE)
```



There is very little change with this deseasoned ACF compared to that of the original series. The PACF does appear to to show that lags are less correlated than that of the original series.